A new era of observationally-infused E3SM: GANs for unifying imagery archives

Jon Schwenk, Earth and Environmental Sciences, Los Alamos National Laboratory
Christopher Ren, Intelligence and Space Research, Los Alamos National Laboratory

Focal Area(s)
This paper primarily addresses Focal Area 3: insight gleaned from complex observed data and big data analytics, although the idea presented is not specifically focused on a single technique to extract insight, but instead aims to explore a new paradigm toward unifying the data from which insight-gleaning techniques are applied.

Science Challenge
This paper presents an idea to develop a "Rosetta Stone" for unifying observations from various satellite or remote sensors into a common format that would vastly advance our ability to exploit existing datasets for improving predictability within Earth System Models (ESMs). While the applications of such a unified archive are broad, we believe it will be a critical step toward ushering in a new generation of ESMs that are richly informed, guided by, and validated by extensive observational data. With the vast quantity of both remotely-sensed and *in-situ* data streams available and coming online, new approaches are needed that can harmonize and thus fully exploit these expensive datasets. While we present the broader idea, we point to examples of applications that impact the water cycle and its representation in ESMs.

Rationale
Observational data are a cornerstone of ESM predictability, providing initial conditions, parameterizations, and bases for measuring performance. The global coverage, frequent return periods, and historic extent of many satellite sensors poises them to play a growing role in addressing these needs. However, in our view, satellite imagery's potential for improving ESM predictability remains heavily underutilized, largely due to sensor shortcomings such as irregular/long revisit times, cloud coverage, etc., and technical challenges arising from managing and manipulating huge datasets and blending information from multiple sensors.

We focus on two primary ways that satellite sensor data are used to inform ESMs. Sensors typically do not directly measure quantities of interest, but instead measure the radiation, or energy, of various wavelengths of the electromagnetic spectrum. In order to obtain useful information, such as sea surface salinity or atmospheric aerosol concentrations, a model must be constructed to predict the variable of interest from the observed radiances. This model is typically an inversion, statistical, or machine-learned model that may be applied to the sensor's historic imagery archive to produce spatially-continuous time series of critical variables. These historical data may serve as initial conditions, be dynamically assimilated into ESMs, or integrated into, for example, the International Land Model Benchmarking (ILAMB) tool as validation datasets. A second way that satellite data are critically important to ESMs lies in efforts to generate subgrid parameterizations of critical processes. For example, ESMs may require the concentration of sea ice in grid cells of the Arctic Ocean or the prevalence of surface waterbodies to characterize land units. In these cases, specific objects (an ice sheet, a lake) are

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identified from the satellite sensor data typically via machine learning. Accurate training data are often expensive and difficult to collect.

These approaches share a key problem: a different model must be developed for each satellite sensor. While the MODIS sensor on the Aqua/Terra satellites and the Operational Land Imager aboard Landsat both return information that can be used to characterize vegetation or delineate waterbodies, a separate model must be developed for each sensor. Double effort must be made to develop the models, collect training data, and solve model parameters for both sensors. Thus the expense of fusing cross-sensor information serves as a major barrier toward fully exploiting the vast archives of satellite data. By harmonizing imagery across sensors, we will also unify the field's parallel efforts toward developing better techniques for extracting or modeling critical features and variables from satellite imagery, as efforts could concentrate on a single, spatiotemporally dense archive.

An additional benefit of this approach lies in the extrapolation of *in-situ* or field data to broader regions via satellite imagery. The DOE invests significantly in field campaigns that feature intense data collection at local sites. The Next Generation Ecosystem Experiments, Atmospheric Radiation Measurements, and Scientific Focus Areas are prime examples of programs that collect rich datasets at typically site-to-regional scales. These *in-situ* data could become immediately more informative and impactful to ESM predictability via extrapolation through satellite imagery. The current barriers are similar to those above but with an additional complication: data must be aligned in both space (easy to do) and time (harder to do) to the corresponding satellite overpass. Long return intervals (> week) such as that of Landsat coupled with cloud cover often result in the discarding of valuable data because of misaligned timing. The improved temporal density of a unified archive and the inclusion of cloud-penetrating sensor types (e.g. radar) in a unified archive will largely alleviate these issues and help fully extract the value of these DOE investments.

Narrative

GANs, briefly. Generative adversarial networks (GANs) have recently been used to tackle the image-to-image translation problem, more commonly known as *domain transfer*. This problem consists of learning a transformation which contains semantic and stylistic characteristics of specific domains. An example is shown below where a GAN has learned to transfer the characteristics of a zebra onto a horse and vice versa. GANs achieve this by representing imagery characteristics in a reduced-dimensional latent space. Training GANs does not require paired data, minimizing one of the bottlenecks of most machine learning techniques: producing high-fidelity training data. Instead, image sets (from the same satellite sensor, for example) are provided to the GAN, which implicitly learns their characteristics.

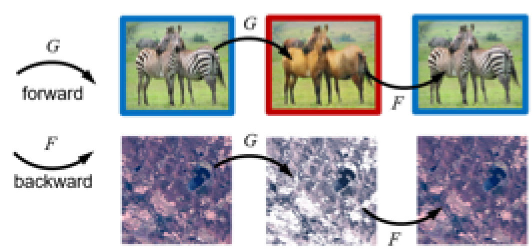

Figure 1: GANs that are effective for translation between domains in natural images (zebra-to-horse-to-zebra) can also be used to generate realistic changes in remote sensing imagery. Here we demonstrate the application of a synthetic snow transformation. The middle snowy image is "artificially" generated by a GAN.

Unifying imagery. GANs may also be taught to transform remotely-sensed imagery in a perceptually accurate manner, even between sensors that measure different portions of the electromagnetic spectrum. This *cross-modality* ability of GAN-based transformations is a cornerstone of this white paper: GANs have shown promise toward translating satellite imagery from different sensors and sensor types (e.g. radar and multispectral) into a common format. The striking result demonstrated by the GAN output in Figure 2 is of a rich, multicolored image that is perceptually similar to that obtained from a multi-band sensor was generated from only a single-band image of radar reflectance. The implication of this ability is that many sensors, regardless of their modality and spectral resolution, may be converted to a common format that still provides rich information from which further insights can be gleaned.

Figure 2: Preliminary results show promise toward converting single-band synthetic aperture radar (SAR) images into richer multiband/multicolor images (GAN output).

Squeezing more out of training data. We have also shown that GANs can be used to implant small, realistic artificial changes as well as larger pervasive ones. In Figure 3, we show a synthetic "vegetation" transformation, with the addition of realistic clouds including cloud shadows. The implications of this capability may also be enormous: the robustness of training datasets may be drastically improved without the need for collecting additional data. For example, consider a non-cloudy Landsat scene over which waterbodies have been identified by hand to train a convolutional neural network (CNN). When the trained CNN encounters a scene with clouds, it will be "confused" as it has not seen clouds previously. However, GANs can be used to synthetically add clouds to the originally-clear image, and the same hand-labeled data can be reused to retrain the CNN, resulting in a model with some degree of cloud-robustness. This idea is extendible beyond just clouds, such that the utility of a limited set of expensively-collected training data may be vastly increased.

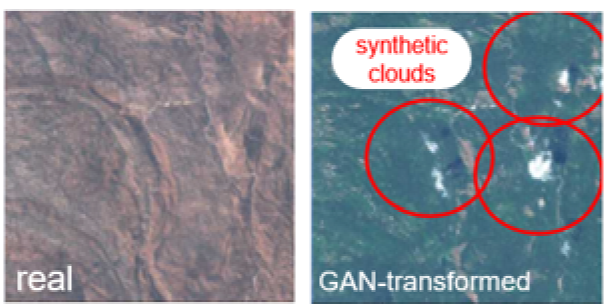

Figure 3: GANs can be used to implant small changes in imagery, such as the clouds and their shadows, as well as pervasive change (unvegetated to vegetated).

Applications to water cycle. Land models within ESMs that solve water balances within each cell require subgrid parameterizations of vegetation, surface water, and land use/land cover properties that change in time. Satellite data have proven enormously useful for solving these parameters. Sea ice plays a critical role in arctic water cycle processes, with remotely-sensed imagery being a primary source of sea ice observations. Cloud coverage and density, rainfall, soil moisture, ground water, snow cover, and reservoir heights each have satellite sensors semi-dedicated to their estimation. Efforts to unify these and other sensors could have wide-reaching benefits across all water cycle components of ESMs.